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VISUAL TEXTURE ANALYSIS: AN OVERVIEW

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ABSTRACT

Over the past 20 years, many measures have been proposed for characterizing and discriminating visual textures. This paper reviews some of these measures, and gives a selected bibliography on the subject.

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1. Introduction

Visual textures are repetitive patterns in which "elements" or "primitives" are arranged according to "placement rules" (see, e.g., [1]). A general model for textures as distorted periodic patterns is given in [2]. Various properties of visual texture have been found useful in pictorial pattern recognition; among these are coarseness (essentially: the size of the "elements") and its variation, if any,with direction. A review of measures that have been used for texture classification can be found in [3].

The importance of visual texture in perception has been recognized for over 25 years. As J. J. Gibson [4] pointed out, a discontinuity in texture coarseness is an important cue for a discontinuity in depth; while changes in texture coarseness across a surface are cues for the slant of the surface relative to the observer. Psychological studies of texture perception have not been limited to the depth cue aspect; for a review of the role of texture in object perception see [5].

This paper briefly reviews some of the basic methods that have been used to characterize and discriminate visual textures. Section 2 discusses the use of the Fourier power spectrum, of second-order gray level statistics, and of first-order local property statistics, for texture description. Section 3 describes methods of segmenting a picture with respect to textural differences, including the detection of "texture edges" and texture gradients. A selected bibliography on these topics is given.

2. Texture description

2.1. Autocorrelation and power spectrum

The oldest attempt to quantify texture coarseness was made 20 years ago in an unpublished M.S. Thesis by Kaizer (see [3] for the reference). He proposed that the coarseness of a pattern can be measured by the rate at which the pattern's autocorrelation drops off from its peak at zero displacement - in particular, by the amount of displacement required to bring the autocorrelation down to $\frac{1}{e}$ times this peak value. Directionality of the pattern can be detected by the directional dependence, if any, of this displacement.

A closely related approach to characterizing the coarseness and directionality of a pattern is to examine the pattern's Fourier power spectrum. For coarse patterns, the power should drop off relatively quickly from its peak at zero spatial frequency, while for "busy" patterns it should drop off more slowly, since high spatial frequencies play a greater role in the Fourier representation of such patterns. Directionality in the pattern should give rise to a directional bias in the rate of dropoff. This approach to texture analysis has been studied by a number of investigators, and has even been implemented commercially (with the Fourier power spectrum computed optically). A representative example of the Fourier approach can be found in [6]. For a more recent use of Fourier texture descriptors in scene analysis see [7].

A difficulty with the autocorrelation and Fourier approaches to texture analysis is that the finiteness of the texture sample being analyzed gives rise to "edge effects". In the

autocorrelation computation, as soon as the pattern is shifted, it partly overlaps the background; and the power spectrum computation is affected by the discontinuities between the pattern and the background. If the discrete Fourier transform is used in these computations, it treats the pattern as periodic, and the shifting as cyclic; but there are still discontinuities between opposite edges of the pattern. This may be the reason why, in comparative studies (e.g., [8]), Fourier-based features have been found to perform more poorly than statistical features. An attempt to reduce edge effects by working with reflected patterns whose opposite edges are identical is described in [9].

2.2. Second-order gray level statistics

Statistics of the gray level probability distribution can also be used to describe textures. First-order statistics, such as the mean and standard deviation of the gray levels in a pattern, give information about the overall lightness (or darkness) and contrast of the pattern; but they tell nothing about how the gray levels are distributed spatially. More significant for texture analysis are second-order statistics, which describe how various pairs of gray levels occur in specified spatial relationships within the pattern.

In the early 1960's, an important paper by Julesz [10] used transition probabilities (from one gray level to another, as the pattern is scanned row by row) to characterize textures. For any two gray levels i and j, the transition probability p(i,j) tells us how often level i and level j occur in horizontally adjacent positions. In a coarse texture, p(i,j) should tend to be high for $|i-j|$ small, and low for $|i-j|$ large; in a "busy" texture, p(i,j) should be relatively high even for large $|i-j|$. Transition probabilities have been used by many investigators to analyze textures, as well as to synthesize them for perceptual experiments. Closely related to the transition probabilities is the distribution of gray level run lengths; if transitions between different gray levels are rare, long runs of constant gray level should be common, and vice versa. For a recent example of the use of run lengths in texture classification see [11].

Gray level transitions can be analyzed in directions other than the horizontal (e.g., [12]), and for pairs of points

that are nonadjacent [13]. For an arbitrary displacement $\delta = (\Delta x, \Delta y)$, let $p_\delta(i,j)$ be the probability that a point having gray level i occurs in position δ relative to a point having gray level j. In the matrix $(p_\delta(i,j))$ the values away from the main diagonal ($|i-j|$ large) will be low for a coarse texture, but higher for a "busy" texture. Thus a measure of the nonuniformity of the element values in this matrix, or of their spread away from the main diagonal, for δ's of various magnitudes, can be used to characterize texture coarseness; while directionally can be detected by using δ's in various directions. A wide variety of such measures have been introduced by Haralick [14]; see also [15-16].

In principle, one could also use third or higher order gray level statistics as texture descriptors. However, it has been shown [10] that differences in such statistics cannot be perceptually discriminated when the first and second-order statistics are equal. Thus the information conveyed by higher-order statistics cannot be important for texture description.

Measurements of second-order gray level statistics will usually be sensitive to differences in first-order statistics; the values of these measurements will change if the pattern being analyzed is made lighter or darker, or its contrast is stretched or compressed. In order to avoid the confounding effects of first-order differences, it is desirable to normalize the given pattern's gray scale. One common way of doing this is to force the pattern to have a specified gray level probability density, e.g., a uniform one (each gray level occurs equally often); see [14-15].

2.3. First-order local property statistics

Another approach to texture description is based on the probabilities with which various local features occu in the given pattern. For example, the degree to which edges [17] or straight lines [18] are present is a useful texture descriptor. One can even use arbitrary local features, which can be chosen to match the given texture classification problem; see [19].

In a coarse texture, there will be relatively few points at which edges occur, but there will be many more in a "busy" texture. This can be measured, e.g., by computing the average value of some edge detection operator over the pattern. Note, however, that such edge values are sensitive to changes in contrast of the pattern, and so should be measured on patterns whose gray scales have been normalized [15], as pointed out at the end of the preceding section.

The standard edge detection operators are based on taking differences between the gray levels of pairs of nearby points. Differences in orthogonal directions can then be combined to obtain the magnitude of the gray level "gradient". To detect directionality in a texture, differences in various directions can be compared. The points need not be near one another; more generally, they can be at an arbitrary relative displacement δ. Rather than using pairs of single points, one can use pairs of averages computed over nonoverlapping neighborhoods; this yields difference values which tend to be less sensitive to noise [8]. The difference values will be sensitive to the size of averaging neighborhood used; in fact, the size for which the difference values are greatest should correspond to the size of the

"elements" in the texture, so that this "best size" can itself be used as a texture coarseness measure [20]. Pairs of averages can also be used, instead of single points, in computing second-order gray level probability matrices [8].

For a given displacement δ, the probability density $p_\delta(k)$ of differences between gray levels of points δ apart is closely related to the matrix of joint gray level probabilities $p_\delta(i,j)$. In fact, $p_\delta(k)$ can be obtained by summing the elements of $(p_\delta(i,j))$ along the line $|i-j|=k$ parallel to the main diagonal. Thus measures of the spread of $p_\delta(k)$ away from the origin (e.g., its second moment) can be used to characterize texture coarseness [8]. The simplest such measure is the mean of $p_\delta(k)$, i.e., the average edge value, as discussed at the beginning of this section. It has been found [8] that measures based on gray level difference probabilities do about as well, in some cases, as measures based on joint probability matrices; and that the mean of $p_\delta(k)$ does as well as other measures.

3. Texture discrimination

Local property measurements can be used not only to classify textures, but to segment a given picture P into regions which differ in texture. Specifically, suppose that two regions differ significantly in the average value of some local property π. If we compute π at every point of P, we obtain a new picture P_π (i.e., the array of π-values) in which the two regions now differ in average "gray level". If we now blur P_π (i.e., compute the average gray level over a neighborhood of every point), we obtain a picture $\overline{P}_\pi$ in which one region is (hopefully) everywhere darker than the other; we should thus be able to separate the two regions by thresholding $\overline{P}_\pi$ appropriately. Some examples of this approach can be found in [21].

The probability density $p(\pi)$ of values of a local property π can serve as a guide to the potential usefulness of π in segmenting the picture P. If $p(\pi)$ is strongly bimodal, one can regard P as a mixture of two populations of points having different ranges of π values. In practice, this bimodality is often hard to detect, because $p(\pi)$ is dominated by low values. This problem can be avoided by computing $p(\pi)$ only for points where the value of π is a local maximum [22].

An analogous approach can be used to detect edges between regions that differ in texture. Indeed, we can construct the picture $\overline{P}_\pi$ exactly as above, and detect the edge between the regions by taking differences between gray levels of points in $\overline{P}_\pi$. These points should be sufficiently far apart to insure that the gray level averages (of points in P_π) which they represent come from nonoverlapping neighborhoods in P_π. Differences in orthogonal directions can be combined to yield the

magnitude of the "gradient" in average value of π. Examples of this approach, including a discussion of how to automatically pick the degree of blurring that should be used at each point, can be found in [23-24]. On computing the magnitude and direction of the texture coarseness gradient across a picture see [25-26].

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